



Systemically modeling the relationship between climate change and wheat aphid abundance

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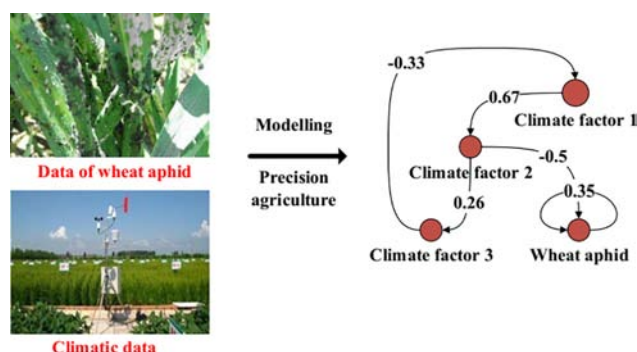
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HIGHLIGHTS

- Fuzzy cognitive map was used to construct a systematical relationship between climate and wheat aphids.
- Temperature exactly influences wheat aphid more than other climate factors.
- Some interrelationship between all kinds of wheat aphid was mined out.
- The relationship between each kind of climate factors was also mined out.
- Natural enemies severely affect wheat aphid.

GRAPHICAL ABSTRACT



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ABSTRACT

Climate change influences all living beings. Wheat aphids deplete the nutritional value of wheat and affect the production of wheat in changing climate. In this study, we attempt to explain the ecological mechanisms of how climate change affects wheat aphids by simulating the relationship between climate and the abundance of wheat aphids, which will not only aid in improving wheat aphid forecasting and the effectiveness of prevention and treatment, but also help mitigate food crises. Fuzzy cognitive maps (FCM) are an effective tool for portraying complex systems. Using *Sitobion avenae* and climatological data collected in China, we made use of differential evolution (DE) algorithms to construct FCM models that directly illustrate the effect of climate on wheat aphid abundance. The relationships among climate and wheat aphids at different growth stages (I–III instar larvae, IV instar larvae with wings, IV instar larvae without wings, adult with wings, adult without wings) were established. The analysis results from the FCM models show that temperature positively influences wheat aphids most. Moreover, these models can be used to determine the numerical value of each climate factor and the abundance of wheat aphids quantitatively. Furthermore, the two overall relationship models between climate and wheat aphids were constructed and the experimental results show that natural enemies and highest daily temperature affect wheat aphids most. Natural enemies and highest daily temperature exert negative and positive impacts on wheat aphids respectively. Some interrelationships among wheat aphids at all growth stages and the internal relationships among climate factors were also shown.

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1. Introduction

How climate change affects biological organisms has become a significant area of research globally especially over the past decade. Over this period of time many advances have been made, including the predictive framework of infectious diseases of natural (Altizer and Harvell, 2013) and agricultural systems (plants and animals) (Ash et al., 2013; Wang et al., 2011); the relationship between climate change and the response of humans towards specific viruses (Morin and Comrie, 2013); which is caused by climate change; the impact of temperature on agricultural systems (Lu et al., 2013) and the relationship between population structure/demographic characteristics and climate change (Ozgul et al., 2010). Insects are poikilothermic, relying on ambient or environmental temperatures to maintain their internal temperature, which means that climate warming directly influences their core life activities (Challinor et al., 2016). Wheat aphids consume wheat and affect its growth, consequently the production amount of wheat will dramatically decrease. Moreover, in recent years researchers have revealed that compared with other environmental and life-history factors, such as UV intensification, the concentration of carbon dioxide, precipitation, the insect's natural enemies and so on, increased temperatures have the greatest effect on the core physiological processes of insects (Ma et al., 2015). At the same time, China is one of the regions where climate warming is most striking (Piao et al., 2010). The previous meteorological records of temperature in northern China have been broken several times and these two decades are becoming the hottest period in China. Severe explosions of wheat aphids have lasted for 20 years, which is consistent with the years when climate warming is evident. In addition, wheat aphids are especially sensitive to high temperatures. Therefore, explaining the ecological mechanism of how climate warming affects wheat aphids and simulating the relationship between climate and wheat aphid can not only help to improve wheat aphid forecasting, prevention and treatment but can also mitigate the food crisis (Godfray et al., 2010). It can also provide a theoretical and methodological framework for studying the occurrence, regularity, and population trends of major diseases and pests in China in the context of climate warming, protecting more grain crops from nibbling and improving the quality of grain crops.

Much research has investigated the relationship between wheat aphids and climate. For example, Hoover and Newman (2004) developed a mechanistic model of the general interactions among grasses, cereal aphids, and their parasitoids, and used this model to investigate the interacting effects of rising CO₂ concentrations and temperature; Nguyen et al. (2009) examined the effects of daily heat fluctuations and UV radiation on the proteome and performance of winged and wingless morphs of the *Macrosiphum euphorbiae*. They found that a daily regime of 4 h of heat stress at 35 °C had more negative effects on the fitness of aphids than a similar period of UV-B stress (11.6 kJ m⁻² per day), and these effects were most pronounced on wingless aphids. In addition, they also found that a reduced performance of aphids under heat stress is correlated with the lower abundance of several enzymes in central pathways of energy metabolism, and several exoskeletal proteins were induced or their abundance increased under high temperature stress. Luo et al. (2013) examined spectral features (SFs) with four methods to detect aphid densities in wheat leaves and established a model to estimate aphid density using partial least square regression (PLSR).

Although many breakthroughs have been made (see the above-mentioned literature), the research methods of previous studies do not regard all climate factors systematically; thus, obtaining a complete relationship that fully characterizes the influence exerted on each factor by itself and the influence exerted by other factors on each factor is difficult. To explore the relationships hidden in the dataset, the current research utilized fuzzy cognitive maps that can effectively model a complex system as the instrument to mine a systematic relationship graph from the dataset. The resulting directed weighted graphs could

be used to analyze which climate factors impact wheat aphids and quantitatively estimate the climate conditions and abundance of wheat aphids. These models can assist with forecasting the amount of wheat aphids and controlling the harm caused by them.

2. Materials and methods

2.1. Dataset

All the winter wheat in all the winter wheat fields grows consistently without spraying pesticide to make *Sitobion avenae* to grow freely. Then the climate factors and the amount of wheat aphids at each growth stage were measured simultaneously. The host plant is winter wheat. The datasets in the present study were collected in the winter wheat production area of China. Though climate is involved in many factors, we measured three climate factors (highest daily temperature, average daily temperature and daily precipitation) and two factors related to wheat aphids (natural enemies and growth stage of wheat) to simplify the research task. We then counted the abundance of wheat aphids at each growth stage (I–III instar larvae, IV instar larvae with wings, IV instar larvae without wings, adult with wings, adult without wings and the total number of wheat aphids).

There were a total of 28 datasets. Six were collected between 2003 and 2004 from Shandong Province; four between 2012 and 2015 from Beijing; one collected in 2008 from Puyang (Henan); six collected between 2008–2009 and 2011–2014 from Hebei province; six between 2008 and 2010 from Linfen (Shanxi); four between 2012 and 2015 from Xinxiang (Henan) and one in 2010 from Anyang (Henan). The locations of all the data acquisition places are shown in Fig. 1.

2.2. Fuzzy cognitive maps

Fuzzy cognitive maps (FCM) (Tsadiras, 2008; Wu and Liu, 2016) are an effective instrument for depicting the mutual effects of factors in a complicated system, where the relationships in FCM include cycles that reflect the loop among some factors and simple paths that reflect the chain of influence among different factors. FCM adopts a directed weighted graph to illustrate the concrete relationships between any pair of factors. Each node in the graph represents a specific factor and the edges between a pair of nodes refer to the influence exerted on one factor by another factor. Negative weights and positive weights in the graph show an inhibition action and a promoting effect respectively, whereas zero signifies that there is no relationship between two factors. Given N variables (factors), FCM can be expressed as a matrix which is shown in Eq. (1) (Wu and Liu, 2016) and whose elements are the weights in the corresponding FCM model.

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{N1} & \cdots & a_{NN} \end{pmatrix}, -1 \leq a_{ij} \leq 1 \quad (1 \leq i \leq N, 1 \leq j \leq N) \quad (1)$$

According to the time series data which is used to construct the FCM, the value of the i th factor at this moment is affected by the values of factors that have nonzero connections to the i th node at the previous moment and can be computed with Eq. (2), where $C_i(t+1)$ and $C_j(t)$ are the value of the i th factor at the $(t+1)$ th moment and the value of the j th factor at the t th moment respectively. a_{ij} and $\delta(x) = \frac{1}{1+e^{-\lambda x}}$ are the element in A which depicts the FCM and transformation function respectively. λ is an algorithm parameter that is similar to the parameter of the activation function in artificial neural network (Li et al., 2018). Because parameter λ is different for different applications, we set $\lambda = 2, 3, 5$ to find the optimal λ for this research.

$$C_i(t+1) = \delta \left(\sum_{j=1}^N a_{ij} C_j(t) \right) \quad (2)$$



Fig. 1. The locations of data collection sites.

$$C_i(t+1) = \delta \left(\sum_{j=1}^N a_{ij} C_j(t) + a_{ij}^2 C_j(t-1) + \dots + a_{ij}^k C_j(t-k+1) \right) \quad (3)$$

In FCM, the value of the j th attribute at the $(t+1)$ th moment depends on the values of the other attributes at the t th moment, but this assumption always limits the application of FCM. Therefore, high-order FCM (Lu et al., 2014), which relies on the assumption that the value of the j th attribute at the $(t+1)$ th moment depends not only on the values of the other attributes at the t th moment but also on the values of the other attributes at the $(t-1)$ th and the additional previous moment comes into being. The difference between k -order FCM and one-order FCM lies only in Eq. (2) and the corresponding Eq. (2) for k -order FCM is shown in Eq. (3). FCM can complete a time series prediction of multiple variables and multiple variable regressions simultaneously, which is impossible to achieve by an ordinary regression model. Because of this advantage, FCM has been applied in many fields to solve practical issues, such as constructing the health, safety and environment management system (HSE-MS) (Kang et al., 2016), building the gene regulatory network (Chen et al., 2015), and constructing breast cancer risk assessment and management model that combines expert knowledge and mammographic image features to predict the breast cancer risk grade along with stakeholder analysis (Hester, 2015). It has also been used in the prediction of users' desirability (Fatahi and Moradi, 2016), industrial marketing planning (Lee et al., 2013), and artificial emotions forecasting (Salmeron, 2012). The architecture of FCM can be built on the basis of some expert knowledge. However, when expert knowledge is lacking or unknown, it is imperative to make use of some algorithms to complete this task.

2.3. Algorithm for learning structure of FCM: differential evolution algorithm

Differential evolution (DE) (Lin et al., 2011; Neri and Tirronen, 2010; Wang et al., 2017) algorithm is a type of evolutionary computational algorithm (Wiecha et al., 2016) that can effectively and efficiently solve numeric optimization problems. It makes use of a virtual population

to form an initial solution space and then recursively implements differential mutation, crossover and greedy selection until the termination condition is met. In this evolution process, the solutions in the population evolve to fit the dataset, and subsequently, the optimal solution that can express the FCM comes into being. In the evolutionary process of DE, the matrix that shows the relationship containing all the factors is transformed into a vector that is called individual in DE to facilitate mutation and crossover. Differential mutation and crossover are implemented according to Eqs. (4) and (5) respectively. In the differential mutation procedure, x_i , x_{r_1} , x_{r_2} , F (an algorithm parameter) and v_i are the original individual, the first randomly chosen individual, the second randomly chosen individual, the scaling factor and the mutation individual respectively (Lin et al., 2011). In the crossover procedure, $x_{i,j}$, $v_{i,j}$, $u_{i,j}$, CR (an algorithm parameter), $rand(0,1)$, $rand(1,N^2)$ and N are the j th element of the i th individual, the j th element of the mutation individual originating from the i th individual, the experimental individual originating from the i th original individual, the crossover factor, a random floating number ranging from zero to one, an integer ranging from 1 to N^2 and the number of variables in FCM. In the greedy selection procedure, the data error (fitness function) is used to evaluate the individual (FCM models). The objective function in this research is shown as Eq. (6), where N_t , N_n and N_s are the number of rows of each dataset, the number of datasets and the number of factors respectively. $C_n^t(s)$ and $\tilde{C}_n^t \sim (s)$ are the value of the s th factor at the t th moment in the n th dataset and the corresponding value returned from FCM respectively. The smaller the data error is, the better.

$$v_i = x_i + F(x_{r_1} - x_{r_2}) \quad (4)$$

$$u_{i,j} = \begin{cases} v_{i,j}, & \text{if } (rand(0,1) \leq CR) \text{ or } (j = rand(1, N^2)) \\ x_{i,j}, & \text{otherwise} \end{cases} \quad (5)$$

$$\min(\text{Data Error}) = \min \left(\frac{1}{(N_t-1)N_nN_s} \sum_{t=1}^{N_t-1} \sum_{n=1}^{N_n} \sum_{s=1}^{N_s} (C_n^t(s) - \tilde{C}_n^t \sim (s))^2 \right) \quad (6)$$

Due to the excellent performance of DE in numeric optimization problems, it has been used to tackle a variety of practical problems, such as the inverse problem of strain distribution in fiber Bragg grating (FBG) (Wen et al., 2008), searching the global alignment of two sets of feature points (Hao et al., 2005), and digital IIR filter design (Karaboga, 2005). The number of steps of iteration in this study is set as 2000, which is sufficient for searching for the optimal solution. At the same time, we also referred to some literature

(Chen et al., 2018; Hong et al., 2018) to determine this algorithmic parameter.

2.4. Experimental settings

All the datasets are formed as time series and some of the datasets came from the same field. All the data were preprocessed with Eq. (7) to normalize the influence of each factor and avoid the dominant factors

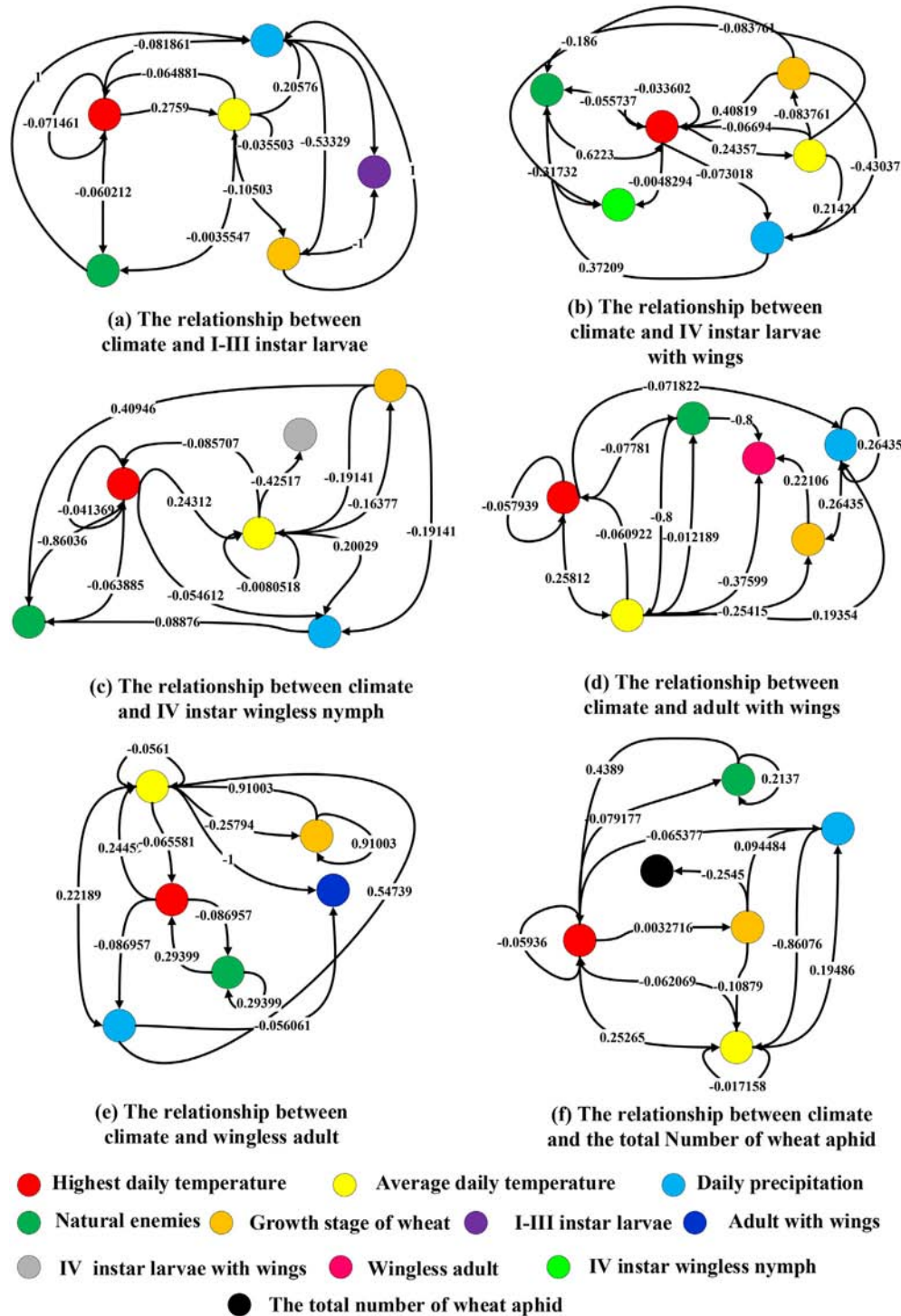


Fig. 2. The relationship between climate and wheat aphids at all growth stages ($\lambda = 5$, three-order FCM). This figure shows the overall relationship between all external factors and wheat aphids at each growth stage (the total number of wheat aphids). These directed graphs can be used to estimate the amount of each factor (including wheat aphids at each stage and the total number of wheat aphids).

Table 1

The number of simple paths in Supplementary Fig. 2. The simple paths were summarized from Fig. 2. The start and end points of each simple path are climatic factors and wheat aphids at different growth stage respectively.

No. of model	The number of simple paths	The highest daily temperature	Average daily temperature	Daily precipitation	Natural enemies	Growth stage of wheat
1 (I–III instar larvae)	20	7	7	1	3	2
2 (IV instar larvae with wings)	34	7	13	3	3	8
3 (IV instar larvae without wings)	16	2	4	2	2	6
4 (adult with wings)	21	9	6	1	4	1
5 (adult without wings)	7	2	1	1	2	1
6 (the total number of wheat aphid)	12	4	3	2	1	2

whose absolute values are much larger than those of the other attributes. a_{ij} , $\hat{a}_{ij}$ and $\max(a_i)$ are the value of the i th attribute (factor, e.g., highest daily temperature) in the j th row (a sample) of a dataset, the corresponding preprocessed value and the maximum value of the i th factor (column) in same dataset respectively.

$$\hat{a}_{ij} = a_{ij} / \max(a_i) \quad (7)$$

There are also some other data normalization methods, such as z-score (Witten, 2003), and the effect of them is similar according to the preliminary experiments which compared z-score and Eq. (7) with a part of dataset. Therefore, we did not talk about data normalization methods more in this study. All the data were randomly divided into two parts (3/4 and 1/4) for training and testing. The final result is the FCM model with minimum data error. Moreover, the parameter λ was set differently for searching for a proper λ ; one-order, two-order and three-order FCM are used to model the relationship between climate and wheat aphids. We designed two experiments: the first was to study the relationship between climate and wheat aphids at each growth stage (I–III instar nymph, IV instar wingless nymph, IV instar alate nymph, wingless adult and alate adult, including the total amount of aphids) without considering the impact exerted on climate by wheat aphids and the heterogeneity from different years; the second was to study the overall relationship between climate and wheat aphids without considering the influence of wheat aphids on climate and the heterogeneity from different years.

3. Results and discussion

3.1. The relationship between climate and wheat aphids at each growth stage

Because differential evolution algorithm is a probabilistic stochastic algorithm, the results for each execution are different. Therefore, the code was repeatedly run ten times and the results (the minimum value, maximum value and mean value of the data error, which can also be regarded as the fitness evaluation function) are shown in Supplementary Table 1. The first study returned six FCM models, which are shown in Fig. 2, and the relevant data error illustrates

which λ is appropriate for the second study. The second study returned two FCM models. In this process, the sparsity of FCM models obtained with differential evolution algorithm is always larger than the FCM models (Stach et al., 2012) in the real world. Therefore, the sparsity of FCM in the present research is limited to 40% according to literature. The results (Supplementary Table 1) reveals that λ is not concerned with the data error of these models, but the higher the order number is, the better the characterization ability of these models.

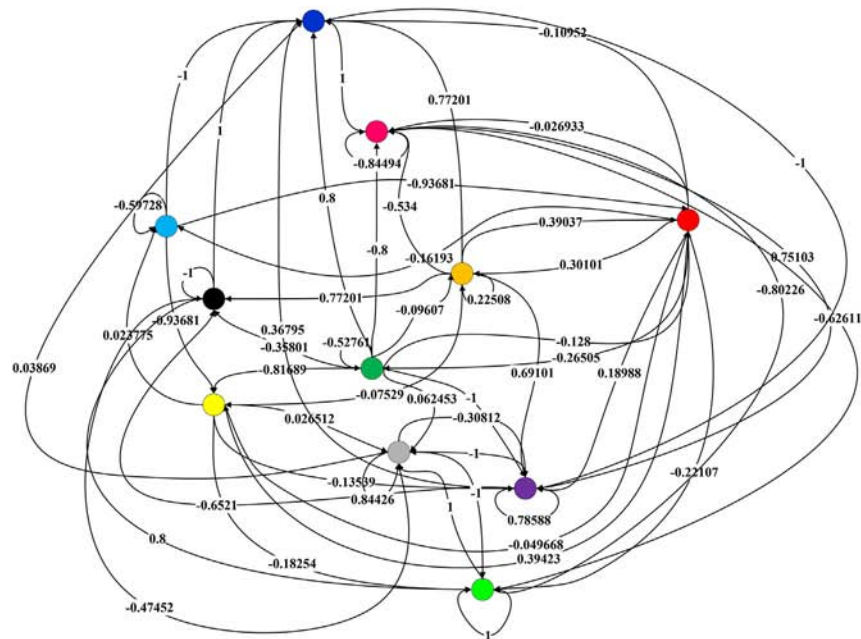
The data error (the fitness function of DE) (Supplementary Table 1) signified that λ does not affect data error significantly. Furthermore, Fig. 2 shows the models that present the relationship between climate and wheat aphids at each growth stage (i.e., I–III instar larvae, IV instar larvae with wings, IV instar larvae without wings, adult with wings, adult without wings) or the total number of wheat aphids. The simple paths, standing for the influence exerted by climate factors on wheat aphids at each growth stage (the total number of wheat aphids) and cycles, whose start point and end point are climate factors in Fig. 2 are shown in Supplementary Figs. 1 and 2 respectively. These simple paths and cycles reveal that climate can affect wheat aphids. Supplementary Fig. 1 shows the loops (Deo et al., 1982) of each model in Fig. 2, which signifies that some climate factors also influence each other mutually. FCM not only depicts the effect of climate factors on wheat aphids but also reflect the impact from one factor to the same factor in the entire system. The matrices corresponding to all subfigures in Fig. 2 are shown in Supplementary Table 2. The simple paths can be divided according to the start point and end point, where the number of simple paths from the highest daily temperature and average daily temperature to the wheat aphids at each growth stage (the total number of wheat aphids) are significantly more than the number of simple paths from other climate factors to the wheat aphids at each growth stage (the total number of wheat aphids). The concrete number of wheat aphids can be estimated using these models and the time series data collected, which can effectively improve the broadcasting power, help farmers to control the amount of wheat aphids and prevent the harm caused by wheat aphids.

The number of simple paths (Hershberger et al., 2007) from the climate factors to the wheat aphids at different growth stages in Supplementary Fig. 2 is shown in Table 1. We also applied degree centrality (Bonacich, 1987; Stephenson and Zelen, 1989) in complex network and graph theory to evaluate the importance of each factor (node)

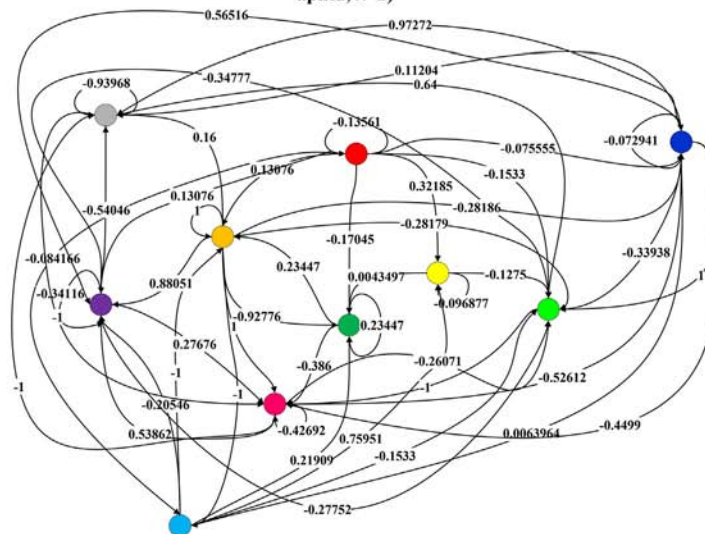
Table 2

The degree of each node in Fig. 2. The out degree and in degree refer to how many edges were from this point to other points and from other points to this point respectively.

No. of model	Degree (out degree/in degree)					
	The highest daily temperature	Average daily temperature	Daily precipitation	Natural enemies	Growth stage of wheat	The number of wheat aphids
1 (I–III instar larvae)	4/2	5/2	2/4	1/2	2/2	0/2
2 (IV instar larvae with wings)	5/4	4/1	1/3	2/3	3/1	0/3
3 (IV instar larvae without wings)	4/2	5/2	2/3	2/2	2/3	0/3
4 (adult with wings)	4/2	5/2	2/3	2/2	1/2	0/3
5 (adult without wings)	4/3	5/4	2/2	2/2	2/2	0/2
6 (the total number of wheat aphid)	5/3	4/3	2/3	2/2	2/2	0/2



(a) The relationship between climate and wheat aphid (with the total number of wheat aphid, $\lambda=2$)



(b) The relationship between climate and wheat aphid (without the total number of wheat aphid, $\lambda=3$)

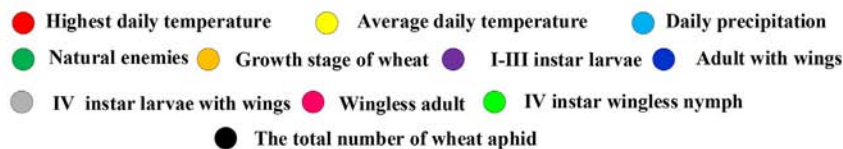


Fig. 3. The relationship between climate and wheat aphids (three-order FCM). This figure sheds light upon the complete relationship between all external factors and wheat aphids at all growth stages, we can find many specific influence exerted by one factor on another factor.

Table 3

The degree of each node in Supplementary Fig. 1. The out degree and in degree refer to how many edges were from this point to other points and from other points to this point respectively.

The highest daily temperature	Average daily temperature	Daily precipitation	Natural enemies	Growth stage of wheat	I-III instar larvae	IV instar larvae with wings	IV instar larvae without wings	Adult with wings	Adult without wings	The total number of wheat aphids
With total number of wheat aphids (out degree/in degree)										
8/4	5/4	4/3	9/2	7/3	4/8	3/6	4/6	4/5	1/8	4/4
Without total number of wheat aphids (out degree/in degree)										
8/1	3/3	6/2	3/5	8/4	4/7	3/8	4/5	5/7	5/7	–

Table 4
Statistical results of simple paths in Fig. 3 (between climate and wheat aphids).

Start point	End point					
	I–III instar larvae	IV instar larvae with wings	IV instar larvae without wings	Adult with wings	Adult without wings	The total number of wheat aphids
With the total number of wheat aphids						
The highest daily temperature	109	115	133	91	237	85
Average daily temperature	129	143	161	95	259	81
Daily precipitation	164	168	194	120	350	116
Natural enemies	211	243	289	177	473	171
Growth stage of wheat	143	158	180	116	308	111
Without the total number of wheat aphid						
The highest daily temperature	456	493	521	414	417	–
Average daily temperature	78	83	93	76	73	–
Daily precipitation	184	197	193	156	161	–
Natural enemies	78	83	93	76	73	–
Growth stage of wheat	98	105	111	78	89	–

(Table 2). The number of simple paths whose start point was highest daily temperature and average daily temperature was significantly greater than the other climate factors, which supports the results from degree centrality as shown in Table 2. The results show that temperature exerts a greater effect on wheat aphids at each growth stage than precipitation, natural enemies and the growth stage of wheat which is calendar dependent. The results shown in Table 1 are consistent with the results in Table 2. The standard deviation of running the model ten times was very small (Supplementary Table 1). We therefore repeatedly ran the code ten times and chose the best result.

3.2. The overall relationship between climate and the total amount of wheat aphids

We also used the same datasets to model the overall relationship between climate change and the total amount of wheat aphids, yielding two models. One model was constructed with considering the total number of wheat aphids and another not. The data error from the models that show the global relationship between the climate factors and the wheat aphids at all growth stages is shown in Supplementary Table 3. The results also verify that λ is not related to the data error, but the order number is more related with data error. The abundance of wheat aphids can also be estimated using these two FCM models and the time series data. The matrices corresponding to the subfigures in Fig. 3 are shown in Supplementary Table 4.

In order to analyze the relationship between the climate factors and wheat aphids, we also applied degree centrality to evaluate the

importance of each factor (node). The relevant results (Table 3) demonstrate the out-degree of the climate factors and the wheat aphids at each growth stage. Moreover, to analyze the relationships, the number of simple paths from the climate factors to the wheat aphids at each growth stage and the simple paths from wheat aphids at one growth stage to another are shown in Tables 4 and 5 respectively. The results show that climate factors exactly influence wheat aphids and that the relationship between wheat aphids at all growth stages is neglected due to the shortcomings of the research method used in previous research. Furthermore, natural enemies negatively affect wheat aphids at all growth stages and the total number of wheat aphids most, which can be observed in the model considering the total number of wheat aphids. The highest daily temperature exerted a more positive influence on the wheat aphids at all growth stages, which is shown in the model without the total number of wheat aphids. In the model considering the total number of wheat aphids, natural enemies were also affected by the climate factors; the number of simple paths from highest daily temperature, average daily temperature, daily precipitation and growth stage of wheat to natural enemies are 1, 2, 2 and 3 respectively.

Because the total number of wheat aphids is the sum of wheat aphids at each growth stage, we constructed two models that illustrate the overall relationship between climate and wheat aphids are shown in Fig. 3, where Fig. 3(a) includes the total number of wheat aphids, whereas Fig. 3(b) does not. The data error of the model without the total number of wheat aphids is smaller than that with the total number of wheat aphids. At the same time, a higher order FCM is more suitable for building this relationship and λ is not related to the data error of

Table 5
Statistical results of simple paths in Fig. 3 (between wheat aphids at different growth stages).

Start point	End point					
	I–III instar larvae	IV instar larvae with wings	IV instar larvae without wings	Adult with wings	Adult without wings	The total number of wheat aphids
With the total number of wheat aphid						
I–III instar larvae	0	3	3	3	8	1
IV instar larvae with wings	4	0	5	1	8	4
IV instar larvae without wings	4	3	0	3	7	4
Adult with wings	4	7	7	0	9	4
Adult without wings	1	3	3	3	0	1
The total number of wheat aphid	9	3	5	3	10	0
Without the total number of wheat aphid						
I–III instar larvae	0	11	8	9	12	–
IV instar larvae with wings	7	0	12	8	8	–
IV instar larvae without wings	15	10	0	10	7	–
Adult with wings	10	11	9	0	8	–
The number of adult without wings	10	13	11	11	0	–

these models. Again, the standard deviation was small when the model was iterated ten times (Supplementary Table 3).

The results in this research are consistent with some above-mentioned literatures, moreover, our studies made these conclusions quantitative. Meanwhile, we found some details that were overlooked previously, such as the relationship between wheat aphids at different growth stages. More climate factors could be considered together and make a global relationship. In addition, we can use this relationship to predict the climate and wheat aphid to construct an automatic dynamic model.

4. Conclusion

In this study, we investigate the impact of three climatic factors (the highest daily temperature, average daily temperature, daily precipitation) on wheat aphids. In the first experiments, the influence exerted on the wheat aphids at each growth stage and the total number of wheat aphids by the climate factors was constructed and the highest daily temperature and average daily temperature exerted exactly a more positive influence on wheat aphids. In the second experiment, two models that can portray the overall relationship between climate and wheat aphids at each growth stage were constructed, where natural enemies and highest daily temperature were more influential than the other factors. Highest daily temperature and natural enemies exerted more positive and negative impacts on wheat aphids respectively. At the same time, the relationship between different kinds of climate factors and the relationships among the wheat aphids at all growth stages are shown. All these results can be employed to forecast the abundance of wheat aphids and to aid in controlling and preventing wheat aphids. Furthermore, these models are able to be exploited to predict the amount of wheat aphids without artificially cutting the relationship among all the factors. In the future, additional relevant factors can be put into the dataset to study the influence of climate on wheat aphids and more data can be taken advantage of to testify the models. In addition, the evolutionary law of the model with time can also be studied by constructing FCM models as a chronological order. Besides, the difference in the models that is related to the difference of locations can also be investigated. Finally, more complex modeling methods may be suitable for solving these problems to find more knowledge about climate and wheat aphids.

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Data availability

The data that support the findings of this study are available from the corresponding authors on request. The model outputs from the FCM constructing program are available to readers on request.

Author contributions

X.Y.L. designed the research; K.Z. conducted the study; K.Z. and J.W.J. collected the dataset; K.Z. and Q.P. were responsible for coding; K.Z., Z.Z.L., X.L. and Q.P. analyzed and finished experimental results; K.Z., J.W.J., Q.P., C.Y.Y. and X.Y.L. co-wrote the manuscript; All authors discussed the results and commented on the manuscript.

Additional information

The authors declare no competing financial interest. Correspondence and requests for materials should be addressed to X.Y.L. (xyliuxidian@163.com).

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2019.04.143>.

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